TOWARDS FUZZY LOGIC IN PARTNER EVALUATION AND SELECTION FOR VIRTUAL ENTERPRISES

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ABSTRACT

The trend where enterprises outsource competencies is getting replaced by strategic alliances, where enterprises work together towards a common goal and share responsibilities as well as their profits. This calls for new ways of organizing work and the technological support that allows flexibility. A Virtual Enterprise (VE) is a temporary organization that pools together different member enterprise core competencies. The construction industry is a key sector in any economy. A construction project is implemented by a team of professionals and an alliance of companies. A crucial competitive factor of a VE, is its ability to form an end-user focused team which can be jeopardized if the right team is not formed. This can be attributed to poor choice of partners for the tasks due to insufficient information available about partners and lack of facilitation techniques. This study proposed definition of multiple criteria decision making problem for construction projects. A multi criteria decision making technique is designed that can be applied to derive each partner's weight and determine the best partner that is eventually selected for each task. A technique that incorporates fuzzy logic in Analytic Hierarchy Process (AHP - a multi criteria decision making technique) to be used by construction industry project initiators to effectively evaluate and select right partners for tasks even when information available about the partners is insufficient is designed and applied. Incorporating fuzzy logic in decision making techniques can address the partners' evaluation and selection process reliability issue.

Keywords: Virtual Enterprises, Multi-criteria decision making, Fuzzy analytical hierarchy process, Partners evaluation and selection problem

INTRODUCTION

Recently, large, medium and small sized enterprises are teaming up to enhance their competitiveness in the market-place and adapt to the rapid changes of technological innovation. Organizations enhance their competitive ability in the market-place by creating effective relationships with others. A Virtual Enterprise (VE) is a temporary organization that pools together different member enterprise core competencies (Crispim and de Sousa, 2009). VEs offer new opportunities (for developing products) to companies operating within an environment with a growing number of participants, such as, contractors, service providers, agencies and others.

A typical application area for the VE paradigm is in industrial manufacturing. Nowadays, most manufacturing processes are not carried out on a single line. Companies tend to focus on their core competencies and join efforts with others, in order to fulfill the requirements of new products and associated services demanded by the market. In a VE, every enterprise is just a node that adds some value to the process. Although most classic examples of cooperative networked organizations can be found in some business domains such as the automotive industry, this tendency is spreading to many other areas including food and agribusiness industry (Camarinha-Matos et al., 1997), electronics (Azevedo et al., 1998) and civil engineering (Zarli and Poyet, 1999).

Similar to manufacturing industries, the need to remain competitive in the market forces service provider companies to seek alliances outside their core competencies when additional skills / resources are needed to fulfill business opportunities. Travel agencies typically offer aggregated or value-added-services with components supplied by a number of different organizations. To "book a complete journey plan", services may include several means of traveling, several hotel bookings, car rentals and leisure tour bookings. A networked cooperation must exist among the many different organizations (Afsarmanesh and Camarinha-Matos, 2000) to enable collaboration.

Building and Construction Industry in Kenya

Kenya has a well-developed building and construction industry with quality engineering, building and architectural design services. The construction industry is a key sector in Kenya economy and has consistently posted high growth (Kenya Economic Survey, 2016; Kenya Economic Report, 2016). The industry also offers direct employment to a significant proportion of the labour force spread throughout the country. The growth in construction in 2016 was 9.2 per cent from an expansion of 13.9 per cent registered in 2015. According to Kenya Economic Survey (2017), there was increased activity in the construction of roads and development of housing that translated to an increase in employment in the sector from 148.6 thousand jobs in 2015 to 163.0 thousand jobs in 2016.

The growth in real estate and the property sector were mainly driven by demand for new office space and urban housing. Among the infrastructure that contributed significantly to this growth were earthworks construction for the Standard Gauge Railway (SGR) between Mombasa and Nairobi, the ongoing construction of roads and energy infrastructure, and expansion of airports.

The improvement of the port of Mombasa also contributed to the sector's growth through the construction work for the second container terminal, infrastructural modifications of berths and construction of a new access road (Kenya Economic Survey, 2016). Reported building plans approved increased in value by 43.3 per cent from KSh 215.2 billion in 2015 to KSh 308.4 billion in 2016. Also reported building works completed decreased in value to 24.7 per cent of the approved building plans in 2016, compared to 32.9 per cent in 2015. There was significant increase in value of public buildings completed from KSh 61.5 million in 2015 to KSh 3.8 billion in 2016. Furthermore, new private buildings in Nairobi City County's value went up by 7.5 per cent from KSh 70.9 billion in 2015 to KSh 76.2 billion in 2016, on account of continued increase in construction of both residential and non-residential buildings. These reports are disseminated in the Kenya Economic Survey (2017).

This sector has attracted a lot of interests from local and foreign investors as seen from the massive projects that have either been completed, are undergoing implementation or are scheduled to take off (World Bank Report [WBR], 2014; Kenya National Bureau of Statistics [KNBS] Report, 2016). Another major beneficiary of the boom in the construction industry was the financial intermediation industry where the commercial banks' loans and advances to construction and real estate sectors grew by 13.6 and 32.4 per cent, respectively, in 2014. Total government expenditure on transport infrastructure was projected to quadruple from KSh 84.5 billion in 2013/2014 to KSh 250.5 billion in 2014/2015 (Kenya Economic Survey, 2015).

In Table 1 presentation of a detailed analysis of selected key economic indicators in the Building and Construction sector for the period 2012 to 2016 is made. The Government expenditure index on roads increased from 350.3 in 2015 to 461.0 in 2016 following an increase in road construction projects. The reported private building works completed in Nairobi City County index rose from 369.4 in 2015 to 407.1 in 2016. Similarly, an increase in the index was registered in public building works reported to have been completed in major towns. This increase was from 112.6 in 2015 to 138.9 in 2016. A rise was also noted in the consumption of cement, a major input in construction of buildings and civil works. Table 1 shows that the rise was by 10.5 per cent from 5,708.8 thousand tonnes in 2015 to 6,302.0 thousand tonnes in 2016. A decrease of credit to the construction industry was marginal to KSh 104.8 billion in 2016 from KSh 106.3 billion in 2015. Employment in the sector grew by 10.1 per cent from 148.1 thousand persons recorded in 2015 to 163.0 thousand persons in 2016.

Table 1. Selected Key Economic Indicators in Building and Construction, 2012-2016 (KNBS, 2017) 1982=100

Indicator/Year	**2012**	**2013**	**2014**	**2015**	**2016***
Index of reported private building work completed in major towns	300.6	321.3	341.4	369.4	407.1
Index of reported public building work completed in major towns	86.9	103.7	106.1	112.6	138.9
Index of government expenditure on roads	449.8	313.9	263.4	350.3	461.0
Index of Employment	175.3	197.8	220.0	245.0	269.9
Cement consumption ('000 tonnes)	3991.2	4266.5	5196.7	5708.8	6302.0
Private Employment ('000)	98.7	112.0	125.3	140.2	155.0
Public Employment ('000)	7.2	7.5	7.6	7.9	8.0
Loans and advances from commercial banks to the sector (KSh Million)	69183	70770	80406	106307	104826

*Provisional. The Index of roads, reported private and public building works completed has been deflated using construction input price indices

A construction project is implemented by a team of professionals and an alliance of companies (Talukhaba, 1999). Alliance of companies is formed by consultants who evaluate contractors for specific project tasks. Consultants are hired by the client to manage the project on their behalf. The needs of the construction industry have been changing from time to time. Talukhaba (1999) while investigating factors causing construction projects delays in Kenya, observed that the factors are associated with the project participants, the process and the environment of project implementation. Factors are poor financial management by clients, inadequate designs and poor management of the construction process by the parties involved in project implementation. These are compounded by poor resource management such as materials and equipment by contractors, inadequate recognition and response to project risks inherent in both the physical and socioeconomic environments of the project, and inadequate regard for the role of project stakeholders by the parties involved in the project implementation process.

THE PROBLEM

The trend where enterprises outsource competencies is getting replaced by strategic alliances, where enterprises work together towards a common goal and share responsibilities as well as their profits. This calls for new ways of organizing work and technological support that allows flexibility. A competitive factor of VE is its ability to form end-user focused team which can be jeopardized if the right team is not formed.

The construction sector's potential contribution to growth of the economy can be enhanced given recent increased expenditure on infrastructure development, if the challenges facing the sector are effectively addressed. Delayed completion of projects (Patroba, 2012), frequent collapse of buildings (Charagu, 2013), lack of ethics (Githui, 2012), use of inappropriate specifications and manuals, incompetent design, poor supervision, use of inappropriate materials, poor coordination and management of contractors (Mambo, 2010), poor construction procedures (Kenya Engineers Report on Projects [KERP], 2006) are among the challenges facing the sector. These can be attributed to poor choice of partners for the tasks due to insufficient information available about partners and lack of facilitation techniques.

This lack of information can be attributed to the sources of information. Project initiators normally use company profiles to evaluate partners (Charagu, 2013). Information from company profiles is often insufficient and decisions made out of insufficient information are subjective. Furthermore, the choices made by project initiators do not take into account that human judgements during partner evaluation and selection are imprecise. This can lead to selection of undeserving partners because partner attributes can change during and/or after the evaluation and selection process, with the qualified partners being unqualified.

Evaluation and selection of a candidate among many alternative contestants is a multi-criteria decision making (MCDM) process (Chena et al., 2009). It has been widely used in various fields such as location selection, information project selection, material selection, management decisions, strategy selection, and problems relating to decision making (Chiou et al., 2005). Selection of best partner among many partners for construction project is an MCDM process.

The study proposes that multiple criteria should be well defined for construction projects so that each prospective partner can be evaluated against each criterion. A multi criteria decision making technique should be designed that can be applied to derive each partner's weight and determine the best partner that is eventually selected for each project task.

Partners' evaluation and selection process reliability for construction projects can be enhanced if decision making techniques that are able to deal with subjective information (Mikhailov, 2003; Covella and Olsina, 2006) are employed. Analytic Hierarchy Process (Saaty and Kearns, 2014), Elimination EtChoix Traduisant la REalite´ (Roy, 1991), Technique for Order Preference by Similarity to Ideal Solution (Lai et al., 1994), Data Envelopment Analysis (Cook et al., 2014), Neural Networks, Weighted Linear Models, Linear Programming, Mathematical Programming (Aruldoss et al., 2013) are among multi criteria decision making techniques. However, they cannot be used to select right partners for construction projects given that company profiles used as sources of information have subjective information.

Incorporating fuzzy logic (Yager and Zadeh, 2012) in decision making techniques can address the partners' evaluation and selection process reliability issue. This study proposes a framework that incorporates fuzzy logic in Analytic Hierarchy Process (AHP - a multi criteria decision making technique) to be used by construction industry project initiators to effectively evaluate and select right partners for tasks and evaluate/predict the partners' performance, even when information available about the partners is insufficient.

Construction Project as a Virtual Enterprise

Projects in the construction sector are implemented by multiple partners. A client hires an architect / consultant who makes designs for the project and engages other consultants to carry out the various tasks. For example, in a building construction project, the main consultant who is normally the architect, contracts civil/structural, electrical, mechanical, plumbing, interior design and landscaping engineers. They work as a team to accomplish the tasks. The main consultant selects the best engineer / engineering firm among many firms who have similar qualifications. These companies coordinate among each other.

Electrical engineering firm does connections to power, wiring, fittings and conduits. Mechanical engineering firm carries out fixing sleeves, fittings among others. Plumbing firm does pipe works, connections to external works among others. Landscaping firm carries out earth works, planting, constructing fountains among others. Interior design firm does partitioning, paint, furnishing and decorations.

METHODOLOGY

Multi-criteria decision making technique is designed and applied to the values assigned to selection criteria and sub criteria by evaluators to select the best partners for each task. This approach is sequential multi-level technique. While selecting the best partners for a particular task in the construction project, the partners' attributes are analyzed and weights assigned. Multi criteria decision making algorithms are used to derive relative weights of partners and checking consistency of evaluators' judgements. Analytical Hierarchy Process (AHP) is an analytical algorithm for data in hierarchical structure. It can be used as an analysis as well as a multi-criteria decision making technique. Multi-level partners' evaluation and selection process is implemented in three cycles (Musumba, 2017; Nyongesa et al., 2017).

First Cycle: Use of AHP - The objective of this cycle is to evaluate the importance of selection criteria, sub-criteria and partners using crisp numerical values. AHP is useful in determining evaluation preferences by a group of evaluators, however, its weakness include giving unreliable results when evaluator judgement is uncertain. Thus, in order to deal with uncertainty during evaluation there is a need for an algorithm, which can cope with this reality.

Second Cycle: Use of Fuzzy AHP (FAHP) - This cycle extends AHP (using fuzzy logic) which is applicable for managing "certain" evaluation judgements, and to imitate the way humans' reason and judge. Human reasoning and judgement during the partner evaluation and selection is subjective and can be said to be "uncertain". Thus, algorithms that can deal with the uncertainty of human judgements will be an improvement on AHP. Fuzzy logic combined with the AHP algorithm can compensate for the weakness of AHP. The algorithm is implemented and the outcomes of the FAHP and AHP are compared. FAHP does not discard priority weights with low numerical values.

Third cycle: Use of industrial case studies to show the applicability of FAHP.

THE ANALYTICAL HIERARCHY PROCESS

The Analytical Hierarchy Process (AHP) (Saaty and Kearns, 2014) is a method for modelling unstructured decision making problems. Unstructured decision making problems are those in which there is not a clear arrangement of the components of the problems. In the construction industry, the partner evaluation and selection problem is unstructured. AHP is a theory of measurement for dealing with quantifiable and intangible criteria that has been applied to numerous areas, such as decision theory and conflict resolution (Vaidya and Kumar, 2006). More and more researchers are realizing that AHP is an important generic method and are applying it to various manufacturing areas (Chan et al., 2000). In addition to the wide application of AHP in manufacturing areas, research and industrial activities of applying AHP on other selection problems are also quite active (Tam and Tummala, 2001).

AHP being a multi-criteria decision making (MCDM) method, uses pairwise comparisons of alternatives to derive weights of importance from a multi-level hierarchical structure of objectives, criteria, sub-criteria and partners. In cases where the comparisons are not perfectly consistent, AHP provides an uncomplicated method for improving the consistency of the comparisons, by using the eigenvalue method and consistency checking method. The hierarchical structure fits well with the hierarchical structure of a partner evaluation and selection problem.

AHP algorithm has the following steps:
i) Define the unstructured problem and state clearly the goal/objectives and outcomes;
ii) Decompose the complex problem into a hierarchical structure of alternatives;
iii) Employ pairwise comparisons of alternatives and form pair-wise comparison matrices;
iv) Use Eigenvalue method to estimate relative weights;
v) Check the consistency of decision judgements;
vi) Aggregate the relative weights to obtain the overall rating for alternatives. These steps of the algorithm can be summarized into three (Vila and Beccue, 1995). Firstly, the problem is decomposed into a number of hierarchical levels. Secondly, data is collected from evaluators, arithmetic mean computed on the values and pairwise comparison matrices are formed. This step reduces the complexity of the multi-criteria multi-decision to a simple set of pairwise comparisons. A rating scale is used to indicate the level of importance/preference of one alternative over another, instead of comparing all alternatives simultaneously. The third step is called synthesization. It is where the overall weights of alternatives in all levels of the hierarchy are obtained.

To summarize, assume you have a hierarchical structure of m alternatives with respect to a specific objective, which must be evaluated using n criteria, denoted C_i(i=1, 2, ...n). Let the weight of criterion C_i with respect to the objective be W_{Ci}. Let the relative weight of alternative k $(1\leq k\leq m)$ with respect to criterion C_i be W_{KCi}. The overall weights, denoted P_i $(1\leq i\leq m)$ of m alternatives with respect to the objective are given by equation 1. It is important to note that W_{Ci} $(1\leq i\leq n)$ are the relative (local) weights of criteria Ci while W_{KCi} are relative weights of alternatives, in this case, the partners. These relative weights are computed for elements at level 1 of the hierarchical structure, then at levels 2, 3 to the last level.

Cheng et al. (1999) identified the following shortcomings of AHP; (i) it is used in nearly crisp decision applications; (ii) deals with unbalanced scale of judgements (1 up to 9); (iii) does not take into account any uncertainty associated when mapping human judgement to a number scale; (iv) the ranking of AHP is imprecise or inexact; (v) the subjective assessment of decision makers, and change of scale have great influence on the AHP outcome. Furthermore, Wang and Chin (2008) found that the increase in the number of attributes geometrically increases the number of pairwise comparisons by $O(n^2/_2)$ which can lead to inconsistency or failure of the algorithm. Also, AHP cannot solve non-linear models (Cheng et al., 1999). In view of these AHP weaknesses, Fuzzy AHP that addresses these challenges is discussed in the following sections.

$$(P_{1\ldots}\ P_m) = (W_{C1}\ \ W_{C2}\ \ldots W_{Cn})\ \ x \begin{pmatrix} W_{1C1\ldots\ldots}\ W_{mC1} \\ W_{1C2\ \ldots\ldots} W_{mC2} \\ \\ W_{1Cn\ \ldots\ldots} W_{mCn} \end{pmatrix} \qquad \textbf{(1)}$$

FUZZY ANALYTICAL HIERARCHY PROCESS

Fuzzy theory has proven advantages for dealing with imprecise and uncertain decision situations and models human reasoning in its use of approximate information (Yager and Zadeh, 2012). Fuzzy set theory implements grouping of data with boundaries that are not distinctly defined. In conventional AHP, the pairwise comparison is established using a nine-point scale which indicates the human preferences between alternatives (Cheng et al., 1999).

The discrete scale of AHP has the advantage of ease of use but, it cannot handle the uncertainty associated with the mapping of evaluators' preferences to a number (Kwong and Bai, 2002). The evaluators' judgements are normally vague and difficult to represent in exact numbers but could best be given as interval judgements than fixed value judgements.

Different types of fuzzy numbers (triangular or trapezoidal) are used to decide the priority of one decision variable over other (Buckely, 1985; Dubois et al., 2000). A triangular fuzzy number (TFN), Ñ is given by a≤ b ≤ c where b, a, and c are the most likely, the lower bounds and upper bounds decision values, respectively (Buckely, 1985; Dubois et al., 2000). Figure 1 shows a fuzzy number, which is characterized by a membership function. It differs from traditional set which defines an element as either belongs or does not belong to a set (i.e. 0 and 1). The fuzzy triangular membership function gives the foundation for defining other types of membership functions such as general triangular function, right-angled triangular function and trapezoidal function. For example when a=b for a right-angled triangular membership function such as (*1, 1, 3*) (Buckley, 1985).

When Saaty's nine scale values are converted into fuzzy numbers and the values used in AHP, the resulting algorithm is Fuzzy AHP (FAHP). There are many types of FAHP algorithms such as: FAHP (with extent analysis) (Chang, 1996; Zhu et al., 1999; Mikhailov, 2003), Fuzzy goal programming (Wang and Fu, 1997; Wang and Chin, 2008) and fuzzy preference programming (Bozdag et al., 2003). This study adopts the FAHP (with extent analysis) algorithm.

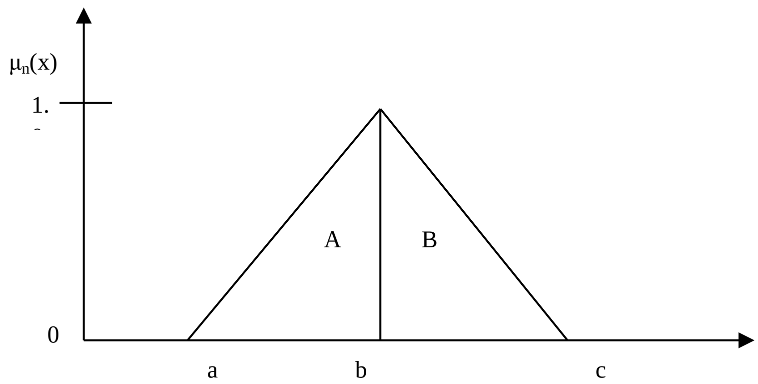

Figure 1. Fuzzy triangular numbers membership

Design of FAHP algorithm for virtual enterprise

This study proposes an algorithm specifically for partner evaluation and selection in the construction sector that incorporates the concept of fuzzy extent analysis in AHP. The proposed FAHP (with extent analysis) algorithm has three steps, which is similar to conventional AHP except that in each step, fuzzy theory is introduced. Fuzzy extent analysis is used to obtain partners' selection criteria relative importance and partner performance preferences (Zhu et al., 1999). Thus, the computation of fuzzy extent analysis results in fuzzy weights.

Steps of proposed FAHP algorithm for this study are:

Step 1. Obtain preference values / level of importance of alternatives. This is done by choosing the linguistic attributes, "Indicating how important each criterion is when your company is selecting partners for structural engineering works in a building construction project" needs an evaluator to choose one answer from (extremely important, very important, important, weakly important and not at all important) to answer.

Step 2. The chosen linguistic attributes are converted into numerical crisp values using Table 2. In the partner evaluation tool, alphabetical symbols (A, B, C, D, E) with matching nominal scales (extremely important, very important, important, weakly important and not at all important) are provided. These are converted to Saaty scale.

Step 3. Once the linguistic opinions are converted to numerical values, computation of the arithmetic mean of the numerical values is done and the averages of crisp values are converted to fuzzy scale using Table 3.

Linguistic symbols obtained from evaluators can be converted directly to TFNs and their arithmetic mean computed. Use of weight mean operator helps to get the collective opinion of all participants. This is done to all lower bound, middle and upper bound triangular fuzzy values. The outcomes of this step are comprehensive fuzzy opinions.

Step 4. Compute the pairwise comparisons matrices of the values of alternatives. This step gives the fuzzy pairwise comparison matrix in form of triangular fuzzy number *(l, m, u).*

Table 2. Crisp Scale

Alphabetical symbol	**A**	**B**	**C**	**D**	**E**
Nominal	Extremely important	Very important	Important	Weakly important	Not at all important
Ordinal scale	5	4	3	2	1
Saaty scale	9	7	5	3	1
Ratio scale	10	8	6	4	1

Table 3. Conversion of nominal or crisp to fuzzy scale

Alphabetical Symbol	**A**	**B**	**C**	**D**	**E**
Nominal scale	Extremely important	Very important	Important	Weakly important	Not at all important
Crisp number	1	3	5	7	9
Fuzzy membership function	(1, 1, 3)	(1, 3, 5)	(3, 5, 7)	(5, 7, 9)	(7, 9, 9)

The pairwise comparison judgement matrix gives the preference of one alternative (A_i) over the other (A_j), and is given by: $A_{ij} = \frac{Ai}{Aj}$ *for i, j =1, 2, 3,...n.* (2)

Step 5. Apply the fuzzy extent analysis to the pairwise comparison matrix. The basic procedures for fuzzy extent are adopted from Zhu et al. (1999) thus,

Let X = $\{x_1, x_2, x_3 \ldots. x_n\}$ be an object set (for this study either the objective, criteria, or sub-criteria) and

G = $\{g_1, g_2, g_3, \ldots g_n\}$ be a goal defined for each level in the hierarchical structure. Thus, G can change depending on the level of the hierarchy.

M extent analysis on each object is taken

$$\acute{M}^1_{gi}, \acute{M}^2_{gi}, \acute{M}^3_{gi}, \ldots\ldots \acute{M}^m_{gi}, \quad i=1, 2, 3, \ldots\ldots, n \tag{3}$$

where $\acute{M}^j_{gi}$ (j=1, 2, 3,…., m) are triangular fuzzy numbers (TFNs).

There are three procedures as explained in the following section for finding extent analysis of objects.

Step 6.1 *First procedure*: The fuzzy synthetic extent value (S) with respect to the i[th] object is defined as,

$$S_i = \sum_{j=1}^{m} \acute{M}^j_{gi} * \left[\sum_{i=1}^{n}\sum_{j=1}^{m} \acute{M}^j_{gi}\right]^{-1} \tag{4}$$

*The symbol * in equation* 4 *is a multiplication operator*

To obtain $\sum_{j=1}^{m} \acute{M}^j_{gi}$, perform the normalized fuzzy addition operation of *m* extent analysis values for a particular matrix such that:

$$\sum_{j=1}^{m} \acute{M}^j_{gi} = \left(\sum_{j=1}^{m} lj, \sum_{j=1}^{m} mj, \sum_{j=1}^{m} uj\right) \tag{5}$$

where *l* is the lower limit (bound) value, *m* is the most promising value and *u* is the upper limit (bound) value. Table 4 is an example of a fuzzy pairwise comparison matrix.

Let *Ob1* represent object *1*, *Ob2* represent object *2* to *Obn* representing object *n*. Additionally, let *Obil* denote the lower TFN value, *Obim* denote the middle TFN value while *Obiu* denote the upper TFN value of the i[th] object. Therefore for *Ob1* in column 1, $\sum_{j=1}^{n} l1$ is found by getting the sum of $(\frac{Ob1l}{Ob1l}, \frac{Ob2l}{Ob1l}, \ldots, \frac{Obnl}{Ob1l})$, $\sum_{j=1}^{n} m1$ is found by getting the sum of $(\frac{Ob1m}{Ob1m}, \frac{Ob2m}{Ob1m}, \ldots, \frac{Obnm}{Ob1m})$ while $\sum_{i=1}^{n} u1$ is found by getting the sum of $(\frac{Ob1u}{Ob1u}, \frac{Ob2u}{Ob1u}, \ldots, \frac{Obnu}{Ob1u})$. The same process is repeated for columns 2, 3 to n for objects 2, 3 to n. Table 4 is then normalized in the same way it is done in conventional AHP. This is done by dividing each fuzzy number in a column with its respective sum of the column. That is lower bound elements are divided by the sum of lower bound elements. Likewise the same is done to middle and upper bound elements.

Let us use $nl_{1,1}$, $nm_{1,1}$ and $nu_{1,1}$ to denote normalized values for column 1 in row 1, $nl_{1,1}$, $nm_{1,1}$ and $nu_{1,1}$ for column 2 in row 1 and $nl_{1,1}$, $nm_{1,1}$ and $nu_{1,1}$ for column 3 in row 1. If similar notations are applied to other rows and fuzzy addition of the rows of the normalized values is done, then results are as shown in Table 5.

Table 4. Fuzzy Pairwise Comparison Matrix

Objective	***Object 1 (Ob1)***	***Object 2 (Ob2)***	***Object n (Obn)***
Object 1	$\frac{Ob1l}{Ob1l}, \frac{Ob1m}{Ob1m}, \frac{Ob1u}{Ob1u}$	$\frac{Ob1l}{Ob2l}, \frac{Ob1m}{Ob2m}, \frac{Ob1u}{Ob2u}$	$\frac{Ob1l}{Obnl}, \frac{Ob1m}{Obnm}, \frac{Ob1u}{Obnu}$
Object 2	$\frac{Ob2l}{Ob1l}, \frac{Ob2m}{Ob1m}, \frac{Ob2u}{Ob1u}$	$\frac{Ob2l}{Ob2l}, \frac{Ob2m}{Ob2m}, \frac{Ob2u}{Ob2u}$	$\frac{Ob2l}{Obnl}, \frac{Ob2m}{Obnm}, \frac{Ob2u}{Obnu}$
…	…	…	…
Object n	$\frac{Obnl}{Ob1l}, \frac{Obnm}{Ob1m}, \frac{Obnu}{Ob1u}$	$\frac{Obnl}{Ob2l}, \frac{Obnm}{Ob2m}, \frac{Obnu}{Ob2u}$	$\frac{Obnl}{Obnl}, \frac{Obnm}{Obnm}, \frac{Obnu}{Obnu}$
Sum	$\sum_{i=1}^{n} l1, \sum_{i=1}^{n} m1, \sum_{i=1}^{n} u1$	$\sum_{i=1}^{n} l2, \sum_{i=1}^{n} m2, \sum_{i=1}^{n} u2$	$\sum_{i=1}^{n} ln, \sum_{i=1}^{n} mn, \sum_{i=1}^{n} un$

Values in the fourth column of the first row are obtained as follows:

$\sum_{j=1}^{m} l1 = nl_{1,1} + nl_{1,2} + \ldots + nl_{1,n}$,

$\sum_{j=1}^{m} m1 = nm_{1,1} + nm_{1,2} + \ldots + nm_{1,n}$,

$\sum_{j=1}^{m} u1 = nu_{1,1} + nu_{1,2} + \ldots + nu_{1,n}$.

Table 5. Fuzzy Addition of Normalized Pairwise Comparison Matrix

	Object 1 (Ob1)	*Object 2 (Ob2)*	...	*Object n (Obn)*	*Fuzzy Addition to obtain* $\sum_{j=1}^{m} \acute{M}_{gi}^{j}$
Object 1 (Ob1)	$nl_{1,1}$, $nm_{1,1}$, $nu_{1,1}$	$nl_{1,2}$, $nm_{1,2}$, $nu_{1,2}$	...	$nl_{1,n}$, $nm_{1,n}$, $nu_{1,n}$	$\sum_{j=1}^{m} l1$, $\sum_{j=1}^{m} m1$, $\sum_{j=1}^{m} u1$
Object 2 (Ob2)	$nl_{2,1}$, $nm_{2,1}$, $nu_{2,1}$	$nl_{2,2}$, $nm_{2,2}$, $nu_{2,2}$	...	$nl_{2,n}$, $nm_{2,n}$, $nu_{2,n}$	$\sum_{j=1}^{m} l2$, $\sum_{j=1}^{m} m2$, $\sum_{j=1}^{m} u2$
...	...	...	...	...	...
Object n (Obn)	$nl_{n,1}$, $nm_{n,1}$, $nu_{n,1}$	$nl_{n,2}$, $nm_{n,2}$, $nu_{n,2}$	...	$nl_{n,n}$, $nm_{n,n}$, $nu_{n,n}$	$\sum_{j=1}^{m} ln$, $\sum_{j=1}^{m} mn$, $\sum_{j=1}^{m} un$
$\sum_{i=1}^{n}\sum_{j=1}^{m} \acute{M}_{gi}^{j}$					$\sum_{i=1}^{n} li$, $\sum_{i=1}^{n} mi$, $\sum_{i=1}^{n} ui$

Similarly, values in the second row are obtained as:

$\sum_{j=1}^{m} l2 = nl_{2,1} + nl_{2,2} + \ldots + nl_{2,n}$,
$\sum_{j=1}^{m} m2 = nm_{2,1} + nm_{2,2} + \ldots + nm_{2,n}$,
$\sum_{j=1}^{m} u2 = nu_{2,1} + nu_{2,2} + \ldots + nu_{2,n}$,

While values in the last row are obtained as:

$\sum_{j=1}^{m} ln = nl_{n,1} + nl_{n,2} + \ldots + nl_{n,n}$,
$\sum_{j=1}^{m} mn = nm_{n,1} + nm_{n,2} + \ldots + nm_{n,n}$,
$\sum_{j=1}^{m} un = nu_{n,1} + nu_{n,2} + \ldots + nu_{n,n}$.

To obtain $\left[\sum_{i=1}^{n}\sum_{j=1}^{m} \acute{M}_{gi}^{j}\right]$, perform the fuzzy addition operation of M_{gi}^{j} (j=1, 2,….m) values such that;

$$\sum_{i=1}^{n}\sum_{j=1}^{m} \acute{M}_{gi}^{j} = \left(\sum_{i=1}^{n} li,\ \sum_{l=1}^{n} mi,\ \sum_{l=1}^{n} ui\right) \quad (6)$$

where;

$\sum_{i=1}^{n} li = \sum_{j=1}^{m} l1 + \sum_{j=1}^{m} l2 + \ldots + \sum_{j=1}^{m} ln$,
$\sum_{i=1}^{n} mi = \sum_{j=1}^{m} m1 + \sum_{j=1}^{m} m2 + \sum_{j=1}^{m} mn$, and
$\sum_{i=1}^{n} ui = \sum_{j=1}^{m} u1 + \sum_{j=1}^{m} u2 + \ldots + \sum_{j=1}^{m} un$

The inverse of this vector is then computed, such that:

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} \acute{M}_{gi}^{j}\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} ui}, \frac{1}{\sum_{i=1}^{n} mi}, \frac{1}{\sum_{i=1}^{n} li}\right) \quad (7)$$

Note: Inverse of a fuzzy number N (l, m, u) is N^{-1} ($^1/_l$, $^1/_m$, $^1/_u$)

Thus equation 7 then becomes:

$$\left(\sum_{j=1}^{m} lj, \sum_{j=1}^{m} mj, \sum_{j=1}^{m} uj\right) * \left(\frac{1}{\sum_{i=1}^{n} ui}, \frac{1}{\sum_{i=1}^{n} mi}, \frac{1}{\sum_{i=1}^{n} li}\right)$$

Recall that if an inverse of a fuzzy number N^{-1} ($^1/_l$, $^1/_m$, $^1/_u$), the value to be multiplied is given in reversed order thus ($^1/_u$, $^1/_m$, $^1/_l$).

The outcome of the first procedure extent values of each alternative which are still fuzzy in nature. These are referred to as blocks of fuzzy extent values. Block 1 is for alternative 1, block 2 for alternative 2 and so on.

Step 6.2 *Second procedure: Layer simple sequencing (Defuzzification of extent analysis values)*

There are two alternatives that can be used to implement this procedure. The first procedure is the original Fuzzy AHP technique. The second procedure is a proposed modification to the Fuzzy AHP.

Step 6.2.1 Alternative one-Fuzzy Synthetic Method.
Fuzzy synthetic method (Mikhailov, 2003) compares each block (alternative) pair by pair towards the overall goal. This gives the sequencing weight vector, V_i, for each block. The same procedure is done when finding the local weights for all levels in the hierarchy.

Bozdag et al. (2003) stated that given two triangular fuzzy numbers $\dot{F}_1(l_1, m_1, u_1)$ and $\dot{F}_2\ (l_2, m_2, u_2)$, the degree *(D)* of possibility that $\dot{F}_1\ (l_1, m_1, u_1) \geq \dot{F}_2\ (l_2, m_2, u_2)$ is defined as:

To explain equation 8, we consider two fuzzy numbers $\dot{F}_1= (l_1, m_1, u_1)$ and $\dot{F}_2= (l_2, m_2, u_2)$. For a sensible comparison between these two fuzzy numbers, it should be investigated both the degree of possibility that $\dot{F}_1$ is bigger than or equal to $\dot{F}_2$ and the degree of possibility that $\dot{F}_1$ is smaller than or equal to $\dot{F}_2$. Let $D\ (\dot{F}_1\geq \dot{F}_2)$ denote the degree of possibility that $\dot{F}_1$ is bigger than or equal to $\dot{F}_2$.

We have three possible cases for $D(\dot{F}_1\geq \dot{F}_2)$:
Case 1: If $m_1\geq m_2$, then we have $D(\dot{F}_1\geq \dot{F}_2)=1$.
Case 2: If $u_1\leq l_2$, then we have $D(\dot{F}_1\geq \dot{F}_2)=0$.
Case 3: For all other possible cases the corresponding degree of possibility is given by:
$D(\dot{F}_1\geq \dot{F}_2) = \frac{l1-u2}{(m2-u2)-(m1-l1)}$

$$D\ (\dot{F}_1 \geq \dot{F}_2) = \begin{cases} 1, & \text{if } m_1\geq m_2 \\ 0, & \text{if } u_1\leq l_2 \\ \frac{l1-u2}{(m2-u2)-(m1-l1)}, & \text{otherwise} \end{cases} \qquad (8)$$

For a logical comparison, Chang (1996) uses the degree of possibility that a fuzzy number $\dot{F}i$ *is* to be greater than *k* fuzzy numbers. This term can be written as follows:

$$D(\dot{F}_i\geq \dot{F}_1,\dots \dot{F}_n) =(D(\dot{F}_i\geq \dot{F}_1) \wedge (\dot{F}_i\geq \dot{F}_2) \wedge,\dots D(\dot{F}_i\geq \dot{F}_n)) \qquad (9)$$

The principle of fuzzy number comparison (Chang, 1996) states that the degree of possibility that a fuzzy number F_i is greater than or equal to a set of fuzzy numbers is equal to the minimum degree of possibility among these values. This is stated as:

$$D(\dot{F}_i\geq \dot{F}_1,\dots \dot{F}_n) = min\ (D(\dot{F}_i \geq \dot{F}_j \mid j=1,2,3\dots, n)) \qquad (10)$$

Consider the synthetic extent values S_i found from matrix of (n x n), then the degree of possibility of the ith alternative is given by: $min(D(S_i\geq S_j| j=1, \dots,n;\ j \neq i)$

Step 6.2.2 Alternative two: Geometric Mean Method (Modified Fuzzy AHP)
For each block, a geometric mean of the fuzzy extent values is computed. This gives the priority vector, V_i, for each block. The same procedure is done when finding the local weights for all levels in the hierarchy. For both alternatives, the non-normalized priority vector for *n* elements becomes:

$$Pv_i' = (h'_1,h'_2.., h'_n)^T \quad i=1, 2, \dots n \qquad (11)$$

where h_i' is the priority vector value for each of the n alternatives.

Step 6.3 Third procedure: Normalizing the sequencing vector obtained in the second procedure. The local weight is found by normalizing the components of this vector using integral value (Liou and Wang, 1992; Bozdag et al., 2003) approach. This approach can be used in computing a wide of range of defuzzification values between 0 and 1 which is similar to the fuzzy state of reasoning of the evaluators.

$$PV_i=h'_i /\textstyle\sum_{i=1}^{n} h'i:\ PV = (h_1,h_2.., h_n)^T. \qquad (12)$$

This becomes the local weight of alternatives in each level of the hierarchy. Global weights for partners are derived by multiplying local weights in lower hierarchy to local weights in the parent elements in the hierarchy. The partner with the highest weight is selected. This method however, is time consuming.

Wang et al. (2006) criticized FAHP with (Extent Analysis) technique and through an example showed that this method cannot estimate true weights from fuzzy comparison matrix. The main criticism revolves around the fact that this method may assign a zero as criterion weight which disturbs the whole decision making hierarchy. The basis of extent analysis theory is that it provides a degree to which one fuzzy number is greater than another fuzzy number, and this degree of greatness is considered as criterion weights. Therefore, if two fuzzy numbers do not intersect then the degree of greatness of one fuzzy number to the other is 100% and therefore it will assign 1 as weight to that criterion while the other criteria will be assigned as zero weight. In light of the above discussion, Wang et.al (2006) summarized the main problems with this method as follows:

i) Once a criteria is assigned a zero weight, it will not be considered in the decision making process.

ii) This method may lose some useful information in the form of judgment ratios in the fuzzy comparison matrices as some of the criterion are assigned zero weight.

iii) It was shown that weights calculated through this method may not represents the true relative importance of that criteria.

iv) This method might select the worst decision alternative as the best one and thus leads to wrong decision making.

Future research should propose techniques that can handle weaknesses of FAHP.

Application of the proposed Fuzzy AHP for virtual enterprise

This algorithm addresses the problem of using crisp values during evaluation and selection of partners. For example, borrowing partners' selection criteria proposed in (Nyongesa et al., 2017), an evaluator might feel that technical skills of a partner are more important than management skills but cannot tell exactly by how much. This data can be represented a range of values (fuzzy/continuous). Suppose averages of evaluators' opinions for business criterion (CN_1), technical criterion (CN_2) and management criterion (CN_3) as presented in (Nyongesa et al., 2017) are 9, 7 and 7 respectively. These crisp values are fuzzified using triangular fuzzy numbers resulting into (7, 9, 9) for CN_1, (5, 7, 9) for CN_2 and (5, 7, 9) for CN_3 respectively. A fuzzy pairwise comparison matrix was formed and extent analysis on the Fuzzy PCM was computed. Table 6 shows the normalized fuzzy pairwise comparison matrix of the selection criteria.

The local weights of each criterion are derived by finding the geometric mean of the fuzzy extent values. It should be noted business criterion sub-criteria were denoted as $SCN_{1,1}$ to $SCN_{1,3}$ for FS, Sp and BS respectively. Likewise, technical criterion sub-criteria were denoted as $SCN_{2,1}$ to $SCN_{2,4}$ for TC, DS, CD and IT respectively. Finally, management criterion sub-criteria were denoted as $SCN_{3,1}$ to $SCN_{3,3}$ for CR, CC and MA respectively. Table 7 shows the outcome when these sample data are subjected to Fuzzy AHP.

Ideally, in any algorithm that ranks alternatives, the sum of the PWs of alternatives should be 1. If this is not the case, then the algorithm has not performed optimally therefore resulting in errors. The higher the error the worse the algorithm's performance becomes. Since the consistency ratio correlate to the judgemental errors in pairwise comparisons (Karlsson et al., 1998; Ahmed and Kilic, 2015), it can be concluded that these mean errors correspond to the consistency ratio (Saaty and Kearns, 2014).

To determine the efficiency of this technique, the same data was applied to AHP technique specialized for virtual enterprise as discussed by both Sanga (2010) and Nyongesa et al. (2017). In order to verify the results of FAHP and as compared to AHP, sources of data is varied from additional five cases of evaluators and projects. Table 8 shows the results of case one. For case 1, P1, P2, P3, P5 and P4 have priority weights in that order with P1 with the highest and P4 with the least. However, this slightly differs from AHP where P4 has a higher weight than P5. AHP has the least error of 0.003 while FAHP has an error of 0.004. This process was repeated for other 4 cases. The arithmetic mean total and errors of the algorithms are shown in Table 9.

Table 6. Normalized Fuzzy Pairwise Comparison Matrix for Criteria

Criteria	CN_1	CN_2	CN_3	Fuzzy Addition
CN_1	0.333, 0.391, 0.412	0.412, 0.391, 0.333	0.412, 0.391, 0.333	1.157, 1.173, 1.078
CN_2	0.333, 0.304, 0.294	0.294, 0.304, 0.333	0.294, 0.304, 0.333	0.921, 0.912, 0.960
CN_3	0.333, 0.304, 0.294	0.294, 0.304, 0.333	0.294, 0.304, 0.333	0.921, 0.912, 0.960
Sum				2.999, 2.997, 2.998
Inverse of sum				0.333, 0.334, 0.334

Table 7. Results of Evaluation using FAHP

Criteria	CN_1			CN_2				CN_3			
CN LW	0.379			0.311				0.311			
SCN	$SCN_{1,1}$	$SCN_{1,2}$	$SCN_{1,3}$	$SCN_{2,1}$	$SCN_{2,2}$	$SCN_{2,3}$	$SCN_{2,4}$	$SCN_{3,1}$	$SCN_{3,2}$	$SCN_{3,3}$	
SCN LW	0.413	0.303	0.282	0.288	0.200	0.140	0.371	0.488	0.280	0.231	
GW	0.157	0.115	0.107	0.090	0.062	0.044	0.115	0.152	0.087	0.072	
											Priority Weights
P1	0.233	0.433	0.285	0.188	0.129	0.250	0.133	0.367	0.200	0.100	0.264
P2	0.167	0.167	0.143	0.250	0.375	0.150	0.267	0.333	0.100	0.400	0.231
P3	0.233	0.111	0.333	0.167	0.115	0.368	0.267	0.211	0.066	0.315	0.214
P4	0.112	0.101	0.154	0.274	0.122	0.211	0.194	0.022	0.289	0.179	0.151
P5	0.155	0.188	0.085	0.121	0.259	0.021	0.139	0.067	0.345	0.006	0.140
										Total	1.000
										Error	0

Note: CN LW denotes criterion local weight
SCN denotes sub criterion
SCN LW denotes sub criterion local weight
GW denotes global weight

Table 8. Case 1: Results of Algorithms

Method	P1	P2	P3	P4	P5	Total	Error
AHP	0.261	0.231	0.229	0.153	0.123	0.997	0.003
FAHP	0.266	0.232	0.214	0.141	0.143	0.996	0.004

Table 9. Arithmetic Mean Total and Error

Method	Case 1	Case 2	Case 3	Case 4	Case 5	Total	Mean Total	Mean Error
AHP	0.997	0.989	0.998	0.996	0.988	4.968	0.9936	0.0064
FAHP	0.996	0.995	0.997	1	0.996	4.984	0.9968	0.0032

From these comparisons, it can be stated that FAHP has average accuracy of 99.68% with a mean error of 0.0032 which is better than AHP which 99.36 % accurate with a mean error of 0.0064. The two techniques are effective but FAHP (with extent analysis) outweigh conventional AHP in terms of generality. This is because FAHP (with extent analysis) can be used when evaluators' judgements are either exact or fuzzy. Apart from the correctness, simplicity and generality of the algorithm, other aspects which can be used to differentiate between the algorithms are time and space complexities.

Time complexity refers to time in which the algorithm runs. It is determined by finding the upper bound on the execution time (Chang, 1996). Chang (1996) found FAHP (for n criteria) has the time complexity of n(n+6) and AHP has a time complexity equal to $\frac{n(n-1)}{2}$. AHP algorithm can be extended to be used in a situation where the evaluators have imprecise information about evaluation judgements. Fuzzy logic can be incorporated in AHP to address the uncertainty of users' judgements during the evaluation of partners. These algorithms gave approximately similar results in all the cases.

CONCLUSIONS

Although Sanga (2010), demonstrated the suitability of AHP in evaluation of alternatives that considers multiple criteria because of its accuracy and flexibility in making a logical, consistent and informed decision, it still cannot deal with subjectivity of human evaluations. AHP deals with crisp values of evaluation and selection judgements. However, human judgements are imprecise, uncertain and fuzzy. Furthermore, when the number of evaluation and selection criteria considered increases, the number of pairwise comparisons increases geometrically. This can lead to inconsistencies or even that the AHP algorithm fails completely. FAHP can address this problem and is proposed as an alternative method for imprecise problems or problems with more criteria. Using AHP in the VE partner evaluation and selection is suitable as it simplifies a complex problem by breaking it up into smaller steps that help in visualizing the problem.

Using FAHP (with extent analysis), it has been shown how preferences can be attained for decision making process, in the partner evaluation and selection problem. It differs from the traditional AHP method, which uses preferences generated from crisp values to evaluate and select partners. The level of accuracy of the prioritization outcome when FAHP (with extent analysis) was used was averagely 99.68% while AHP was 99.34%. It can be stated that FAHP (with extent analysis) can be incorporated in the design and development of new techniques for the VE partner evaluation and selection.

This research proposes that techniques which mimic the way evaluation judgements are done by humans, showing how the use of multi-criteria decision making algorithm and fuzzy models can be developed. The traditional solutions using classical set theory have proved not to be conforming to reality, the way human beings rate partner during evaluation. Instead of having only two choices of instances (for example, 0 or 1, true or false, yes or no), human beings rate events or phenomena in many ways (for example, yes, may be, no). The use of fuzzy logic can address the uncertainty, incompleteness of information, randomness of ideas and imprecision of phenomena.

This study examined multi-criteria decision making (MCDM) “under uncertainties”, in particular the linguistic uncertainties and proposes the incorporation of fuzzy logic in AHP algorithm thus addressing issues of partner evaluation and selection while information available about partners is subjective. There is a great need for the development of techniques for solving evaluation and selection problems (Chou et al., 2008). The computer societies of academics, scholars and researchers have come up with new approaches to address this problem. These new approaches were published in the IEEE computational intelligence journal and IEEE computational intelligence magazine (Bonissone et al., 2009). In a recent publication in IEEE‘s computational magazine the MCDM and fuzzy modelling have been identified by researchers as methods to solve hard science problems (if it can well be incorporated into decision support system).

RECOMMENDATIONS

An avenue for future study is to consider the design and development of techniques that could be used for partner evaluation and selection problems in general. That research should be carried out to determine the applicability of this proposal to other industries and other research fields. Simulations should be done in varying scenarios to determine its weaknesses and recommendations of the proposal for its improvement. In this regard, views of all professionals in the construction industry should be considered to develop a model. This will increase acceptability of the technique in the industry.

REFERENCES

Afsarmanesh, H., and Camarinha-Matos, L.M. 2000. Future smart-organizations: A virtual tourism enterprise. In: Web Information Systems Engineering, 2000. Proceedings of the First International Conference on Web Information Systems Engineering. IEEE Computer Society Press, Hong Kong, 1:456-461.

Ahmed, F., and Kılıç, K. 2015. Modification to fuzzy extent analysis method and its performance analysis. In: Proceedings of the 6th IESM Conference, Seville, Spain

Aruldoss, M., Lakshmi, T. M., and Venkatesan, V.P. 2013. A survey on multi criteria decision making methods and its applications. American Journal of Information Systems, 11:31-43.

Azevedo, A.L., Sousa, J.P., Bastos, J.A., and Toscano, C. 1998. A distributed order promise and planning system for the virtual enterprise. In: Globalization of Manufacturing in the Digital Communications Era of the 21st Century. Springer US, 69-80.

Bonissone, P., Subbu, R., and Lizzi, J. 2009. Multi Criteria Decision Making: A Framework for Research and Applications. IEEE Computational Intelligence Magazine, 43:48-61.

Bozdag, C., Kahraman, C., and Ruan, D. 2003. Fuzzy group decision making for selection among computer integrated manufacturing systems. Computers in Industry, 511:13-29.

Buckley, J.J. 1985. Fuzzy hierarchical analysis. Fuzzy sets and systems, 173:233-247.

Camarinha-Matos, L. M., Carelli, R., Pellicer, J., and Martin, M. 1997. Towards the virtual enterprise in food industry. In: Re-Engineering for Sustainable Industrial Production. Springer US, 73-84.

Chan, F.T.S., Jiang, B., and Tang, N.K.H. 2000. Development of intelligent decision support tools to aid the design of flexible manufacturing systems. International Journal of Production Economics 65(1):73–84.

Chang, D.Y. 1996. Applications of the extent analysis method on fuzzy AHP. European Journal of Operational Research. 953:649–655.

Changkong, V., and Haimes, Y. 1983 Multi-objective Decision Making. North-Holland Series in System Science and Engineering, Elsevier Science.

Charagu, S. N 2013. Collapsing Building Structures in Kenya. In: Proceedings of the 20th Engineers International conference. Tom Mboya Labour College, Kisumu, Kenya.

Cheng, C., Yang, K. L., and Hwang, C. 1999. Evaluating attack helicopters by AHP based on linguistic variables weight. European Journal of Operational research, 1162:423-435.

Chiou, H.K., Tzeng, G.H., and Cheng, D.C. 2005. Evaluating sustainable fishing development strategies using fuzzy MCDM approach. Elsevier , 33(3):223-234.

Chou, S.Y., Chang, Y.N., and Shen, C.Y. 2008. A fuzzy simple additive weighting system under group decision-making for facility location selection with objective/subjective attributes. European Journal of Operational
Research, 1891:132-145.

Cook, W.D., Tone, K., and Zhu, J. 2014 Data envelopment analysis: Prior to choosing a model, OMEGA, 44:1-4.

Covella, G.J., and Olsina, L.A. 2006. Assessing quality in use in a consistent way. In: Proceedings of the 6th International Conference on Web Engineering. Palo Alto, California, USA: ACM Press, New York, NY, 1-8.

Creswell, J. 1994. Research design: Qualitative and quantitative approaches. Thousand Oaks, CA: SAGE.

Crispim, J.A., and Pinho de Sousa, J. 2009. Partner selection in virtual enterprises: A multi-criteria decision support approach. International Journal of Production Research, 4717:4791-4812.

Dubé, L., and Paré, G. 2003. Rigor in information systems positivist case research: current practices, trends, and recommendations. MIS quarterly, 597-636.

Dubois, D., Kerre, E., Mesiar, R., and Prade, H. 2000. Fuzzy interval analysis. In Fundamentals of fuzzy sets. Springer US, 483-581.

Fielding, N., and Fielding, J. 1986. Linking data. Newbury Park, CA: Sage Publications.

Gable, G. G. 1994. Integrating case study and survey research methods: an example in information systems. European Journal of Information Systems, 32:112-126.

Githui, D.M. 2012. Ethical Issues in the Construction Industry in Kenya: A Critical Analysis of the Professional Conduct in Engineering Technology Management.

Glaser, B. G., and Strauss, A. 1967. The discovery of grounded theory: Strategies for qualitative research. Chicago: Aldine.

Guerra, M.A.P. 2006. Analysis and design of virtual enterprises. Doctoral dissertation, University of Saskatchewan.

Johnson, R.B., and Onwuegbuzie, A.J. 2004. Mixed methods research: A research paradigm whose time has come. Educational Researcher, 337:14-26.

Karlsson, J., Wohlin, C., and Regnell, B. 1998. An evaluation of methods for prioritizing software requirements. Information and Software Technology, 3914(25):939-947.

Kenya Economic Report 2015. Available at http://www.kippra.org/downloads/Kenya Economic Report 2015.pdf Retrieved July 2015.

Kenya Economic Survey Report Highlights 2016. Ministry of Devolution and Planning. Kenya Economic Survey 2017. Available at http://www.devolutionplanning.go.ke/images/hb/Economic%20Survey%202017.pdf Retrieved August 2017.

Kenya Engineers Reports on projects KERP, 2006. Ministry of Public works. Available at: http://www.publicworks. go.ke. Retrieved January 2013.

Kenya National Bureau of Statistics 2016. Economic Survey. Nairobi: Government Printer.

Kenya National Bureau of Statistics 2017. Economic Survey. Nairobi: Government Printer.

Kwong, C., and Bai, H. 2002. A fuzzy AHP approach to the determination of importance weights of customer requirements in quality function deployment. Journal of Intelligent Manufacturing, 135:367–377.

Lai, Y., Liu, T., and Hwang, C. 1994. Topsis for MODM. European Journal of Operational Research, 63:486-500

Lincoln, Y.S. 2001. Varieties of validity: Quality in qualitative research. Higher Education-New York-Agathon Press Incorporated, 16:25-72

Liou, T., and Wang, M. 1992. Ranking fuzzy numbers with integral value. Fuzzy Sets and Systems, 50247–255.

Mambo, S. 2010. Why Engineering Structures Fail. Journal of the Institute of Engineers of Kenya, 312:28-29.

Merriam, S. 1988. Case study research in education. San Francisco, CA: Jossey-Bass.

Mikhailov, L. 2003. Deriving priorities from fuzzy pairwise comparison judgements. Fuzzy Sets and Systems, 1343, 365-385.

Musumba, G. W. 2017. Modelling virtual enterprises using a multi-agent systems approach: Case of construction industry in Nairobi County Kenya Doctoral dissertation.

Myers, M. D., and Newman, M. 2007. The qualitative interview in IS research: Examining the craft. Information and Organization, 171:2-26.

Nyongesa, H. O., Musumba, G. W., Chileshe, N. 2017. Partner selection and performance evaluation framework for a construction-related virtual enterprise: a multi-agent systems approach. Architectural Engineering and Design Management, 1-21.

Patroba, H. 2012. China in Kenya: Addressing Counterfeit Goods and Construction Imbalance in Kenya.

Roy, B. 1991. Outranking approach and the foundations of ELECTRE methods. Theory and decision, 311:49-73.

Saaty, T. L., and Kearns, K. P. 2014. Analytical planning: The organization of system, 7. Elsevier.

Sanga, C. 2010. *A technique for the evaluation of free and open source e-learning systems* Doctoral dissertation, University of the Western Cape.

Talukhaba, A. A. 1999. An investigation into factors causing construction project delays in Kenya. Case study of high rise building projects in Nairobi Doctoral dissertation, University of Nairobi.

Tam, M.C.Y., and Tummala, V.M.R. 2001. An application of the AHP in vendor selection of a telecommunications system. Omega 29:171–182.

The Standard Tender Documents, issued by Public Procurement and Oversight Authority in January, 2007. Available at http://ppoa.go.ke/downloads/standard-tender-documents

Vaidya, O. S and Kumar, S. 2006. Analytic hierarchy process: An overview of applications, European journal of operational research 169:1- 29.

Vila, J., and Beccue, B. 1995. Effect of visualization on the decision maker when using analytic hierarchy process. In: System Sciences, 1995. Proceedings of the 28th Hawaii International Conference on System Sciences. IEEE, 4:992-1001.

Wang, H. F., and Fu, C. C. 1997. A generalization of fuzzy goal programming with preemptive structure. Computers and Operations Research, 249:819-828.

Wang, Y. M., and Chin, K. S. 2008. A linear goal programming priority method for fuzzy analytic hierarchy process and its applications in new product screening. International Journal of Approximate Reasoning, 492:451-465.

Wang, Y. M., Elhag, T. M. S., and Hua, Z. S. 2006. A modified fuzzy logarithmic least squares method for fuzzy analytic hierarchy process. Fuzzy Sets and Systems, 157:3055-3071.

World Bank Report 2014. Accelerating growth and poverty reduction in new Kenya. Kenya Economic Update, 10.

Yager, R.R., Zadeh, L.A. 2012 (Eds.). *An introduction to fuzzy logic applications in intelligent systems*. Springer Science and Business Media, 165.

Yaghini, M., Bourouni, A., and Amiri, R.H. 2009. A Framework for Selection of Information Systems Development Methodologies, Computer and Information Science, 21:3-11.

Yu, P.L. 1985. Multiple-Criteria Decision Making: Concepts, Techniques and Extensions. Plenum Press, New York.

Zarli, A., and Poyet, P. 1999. A framework for distributed information management in the virtual enterprise: The VEGA project. In Infrastructures for Virtual Enterprises. Springer US, 293-306.

Zhu, K., Jing, Y., and Chang, D. 1999. A discussion on extent analysis method and applications of fuzzy AHP. European Journal of Operational Research, 116:450-456.